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**MEASURING ROUTE PASSENGER LOAD DIVERSITY FOR CAPACITY AND QUALITY OF
SERVICE ASSESSMENT**

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ABSTRACT

This paper develops theory that quantifies transit route passenger-relative load factor and distinguishes it from occupancy load factor. The ratio between these measures is defined as the load diversity coefficient, which as a single measure characterizes the diversity of passenger load factor between route segments according to the origin-destination profile. The relationship between load diversity coefficient and route coefficient of variation in occupancy load factor is quantified. Two tables are provided that enhance passenger capacity and quality of service (QoS) assessment regarding onboard passenger load. The first expresses the transit operator's perspective of load diversity and the passengers' perspective of load factor relative to the operator's, across six service levels corresponding to ranges of coefficient of variation in occupancy load factor. The second interprets the relationships between passenger average travel time and each of passenger-relative load factor and occupancy load factor. The application of this methodology is illustrated using a case study of a premium radial bus route in Brisbane, Australia. The methodology can assist in benchmarking and decision making regarding route and schedule design. Future research will apply value of time to QoS measurement, reflecting perceived passenger comfort through crowding and average time spent aboard. This would also assist in transit service quality econometric modeling.

Keywords: Transit, Bus Route, Capacity, Quality of Service, Load Factor, Passenger, Operator

INTRODUCTION

The Transit Capacity and Quality of Service Manual (1) and Vuchic (2, 3) underpin deterministic capacity performance analysis for urban transit systems. Measures describing productive performance of an individual transit service or a whole line are useful to operators in quantifying their resources' capabilities and passenger quality of service. Bunker (4) extended productive performance measures to quantify efficiency and operating fashion of transit services and lines, demonstrating their usefulness in planning, design, and operational activities. Automatic Fare Collection weekday data on a premium bus route in Brisbane, Australia, was applied in (5) using measures of occupancy load factor and passenger average travel time to investigate correlation between transit route passenger loading and travel time and its implications on quality of service (QoS) and resource productivity. This paper advances our understanding of passenger capacity and QoS by quantifying passenger-relative load factor and distinguishing it from occupancy load factor. The ratio of these measures is defined as route passenger load diversity coefficient. It then presents methodology to enhance passenger capacity and QoS assessment, using service levels from both passengers' and operator's perspectives. A case study illustrates the application of the methodology.

DEFINITIONS AND LITERATURE REVIEW

General

This paper defines a *service* as a transit vehicle traversing a transit route for the purpose of transporting passengers, according to a published schedule and specified stopping pattern. It defines an *operator* as a transit agency or delegated contractor, which is responsible for operating all of the services along a route or line.

Passenger Loading Measures

Vuchic (2) defines *load factor* at a point as the ratio of passengers transported to spaces offered at maximum schedule load (MSL) whereas the Transit Capacity and Quality of Service Manual (1) defines it as the ratio of passengers transported to available seats. This paper uses Vuchic's definition as it is a normalized volume/capacity measure that cannot ordinarily exceed 1.0 for a given transit vehicle.

Fu *et al* (6) view efficiency of a system from two different perspectives; economically and technically. While economic efficiency measures the relationship between the *values* of output and input, technical efficiency directly compares output and input. They report a range of common, implicit technical efficiency measures for urban transit, including service utilization efficiencies of passenger trips per hour, passenger trips per capital, and km per vehicle. In contrast Bunker (5) examines the physical system of operation of a transit service or line, where input and output measures have the same quantity and units, and the two technical efficiencies considered are explicit, using the measure of *occupancy load factor*.

Passenger Load Diversity along Route or Line

Passenger demand spreads out in time and space, which prevents offered transit point capacity from being fully useable throughout the peak period (5) and along the entire route or line. Temporal variation at a given point has been accommodated broadly in capacity analysis by the Peak Hour Factor, while in QoS analysis TCQSM discusses how passenger loading standards can be expressed as an average during a peak 15, 30, or 60min period (1).

Spatial diversity can manifest itself through variation in passenger loads due to boarding and alighting patterns along the route or line, and to loading diversity within transit vehicles. Vuchic (2) overcomes the point capacity limitation by evaluating a line by segment. Maximum load can ordinarily be achieved only on the Maximum Load Segment (MLS). Utilized transit work provides the operator a picture of total transit performance along the line during a time period. Bunker (4, 5) similarly considers all individual services and passenger patterns at stops during the distance-time window.

Hassold and Ceder (7) consider spatial and temporal diversity by focusing on the determination of daily, hourly and individual service maximum load points in timetable creation using a multi-objective

optimisation network approach. Criteria include wait time, empty-seat km, and empty-seat hours. With respect to demand data for determination of maximum load points, they consider random passenger arrivals for wait time estimation, but use either actual point checks or AFC data for load profiles. This approach is very promising in its consideration of passenger QoS in scheduling, particularly by considering the temporal dimension, although it is not a precise methodology for QoS assessment of an existing route.

Effects of High Passenger Load Conditions

Pass-ups occur when passengers are left behind when a service departs under maximum schedule load. The effective service frequency for these passengers is reduced, as they are forced to wait for the next service or find another means of making their trip (1). This can give rise to multiple maximum load segments and disparity in schedule keeping between services along the route or line causing bus bunching. Ji and Zhang (8) use time gaps between consecutive buses to specify holding times of buses at stops in order to prevent bunching. They argue that time gaps capture the time and space variations of bus speeds and passenger demand. Other headway management strategies have been investigated to reduce adverse impacts of bunching (9, 10).

Passengers' perception of travel time varies depending on conditions being experienced, in particular on-board passenger loading and duration of travel. Although research reveals that valuing individuals' travel time is complex and can depend upon many factors such as location, trip purpose and mode (11), single point estimates of in-vehicle Value of Time (VoT) as a percentage of prevailing wage rate are useful in illustrating the effect of conditions experienced on passengers' travel time perceptions.

VoT established by Concas and Kolpakov (12) for transit in-vehicle seated varies between 25% and 35%, while VoT for transit standing is 50% or up to twice that of seated, and VoT for transit in-vehicle crowded is 100% or up to four times that of seated. These values are quoted in (1) as typical VoT for different types of travel.

According to (1) longer distance trips are generally agreed to attract a higher unit rate VoT; the longer the trip to be made, the more value the average passenger will place on reducing the travel by a single unit of time. While recommended values and elasticities vary widely between studies, the literature suggests that further research is necessary to examine the influence of passenger travel time on VoT, and hence perceived QoS.

Tirachini *et al* (13) examine the multiple dimensions of passenger crowding related to transit demand, supply and operations, including amongst other effects, travel time reliability, passengers' wellbeing, valuation of waiting time and in-vehicle time savings, frequency and vehicle size. They argue that because the crowding externality increases the marginal cost of travel, it should be accounted for in transit system design. Using multinomial nested logit mode choice modelling, they estimate crowding externalities for transit services in Sydney, Australia to show the impact of crowding on the estimated value of in-vehicle time savings and demand prediction, and find that if transit demand is estimated without explicitly considering crowding as a source of disutility to passengers demand will be over-estimated if the service is designed to have a number of standees beyond a threshold. Directions for further research include the effects of crowding on reliability, the connection of crowding to QoS and supply levels in the context of virtuous and vicious circles of transit, differences in socio-demographic perceptions, studying the psychological aspects that influence perception of crowding linked to perception of time, willingness to pay for reduced time spent in crowded environments including in vehicles.

Bunker (5) investigated whether the temporal measures of a route's occupancy load factor and passenger average travel time might be more robust means of characterizing passenger load comfort QoS than the extant point based approach. This paper continues by reconsidering the average load factor actually experienced by passengers along a route during a distance-time window or on an individual service. In doing so, it offers new tools which can be used to better appreciate passenger load comfort QoS and capacity utilization assessment from both the passengers' and operator's perspectives.

Transit Analysis using Electronic Data

Use of Automatic Vehicle Location and Automatic Passenger Counters data is ubiquitous in transit research. Carrasco demonstrates that AVL data can be used to depict transit service reliability including location of reliability problems (14). Furth *et al* (15) provide guidance on the use of this data in improving transit performance and management by examining crowding. Sun and Xu contend that AFC has provided transit agencies with huge amounts of operational data, which have the potential to serve functions beyond the designated purpose of revenue management (16). They show that this data lends itself well to travel time reliability analysis as a QoS problem.

THEORY

Consider distance-time window Z existing on the trajectory plane of the entire length of Route R , during a time period of constant duration such as one hour. This time period of interest is referenced to a location on the plane, such as terminus departure hour, but moves forward along the plane with distance, enveloping the paths of individual bus services of interest. The slopes of the leading and trailing edges of window Z on the trajectory plane are such that, for each segment i of route R , the set of consecutive services of interest k equals 1 to m , which traverse route R during the time period, are contained within Z .

Bunker (5) defines *occupancy load factor* (p/sp), of transit route R within distance-time window Z according to:

$$LF^{occ}_{R,Z} = \frac{\sum_{k=1}^m (\sum_{i=1}^n (t_{k,i} P_{OB,k,i}))}{\sum_{k=1}^m (P_{MSL,k} \sum_{i=1}^n t_{k,i})} \quad (1)$$

Where:

$t_{k,i}$ = scheduled (or actual) segment time for k^{th} service to complete segment i (min)

$P_{OB,k,i}$ = passengers on board k^{th} service on segment i (p)

$P_{MSL,k}$ = maximum scheduled load of transit vehicle applied to service k (p)

By extension, this paper defines the *coefficient of variation in occupancy load factor* for transit route R within distance-time window Z according to:

$$LF^{occ}_{cv,R,Z} = \frac{1}{LF^{occ}_{R,Z}} \sqrt{\frac{\sum_{k=1}^m \left(\sum_{i=1}^n \left(t_{k,i} \left(\frac{P_{OB,k,i}}{P_{MSL,k}} - LF^{occ}_{R,Z} \right)^2 \right) \right)}{\left(\sum_{k=1}^m (\sum_{i=1}^n t_{k,i}) \right) - 1}} \quad (2)$$

Occupancy load factor characterizes occupancy of available transit time-spaces averaged along route R with respect to the time axis of the trajectory plane containing Z . By definition, occupancy load factor of a given service is directly relative only to an observer who is aboard throughout its entire run within distance-time window Z , such as the bus driver. By extension, route R 's occupancy load factor during Z is directly relative only to its bus drivers, who collectively are representative of the route's operator.

It was argued by Bunker (5) that passengers should perceive crowding during their time spent aboard the transit service more so than distance traveled, thus occupancy load factor is a more direct passenger comfort QoS measure than distance based load factor. However, unless the service is point to point, occupancy load factor is not directly relative to the passengers. This is because each passenger

experiences a particular load factor for each segment they traverse only between their boarding stop and alighting stop.

For passenger comfort QoS measurement, however, further understanding can be gained of average load factor relative to all passengers. This paper defines *passenger-relative load factor* (p/sp) of transit route R within distance-time window Z as the average load factor across all passenger minutes travelled along route R with respect to the time axis of the trajectory plane containing Z , according to:

$$LF^{pr}_{R,Z} = \frac{\sum_{k=1}^m \left(\frac{1}{P_{MSL,k}} \sum_{i=1}^n (t_{k,i} P_{OB,k,i}^2) \right)}{\sum_{k=1}^m \left(\sum_{i=1}^n P_{OB,k,i} t_{k,i} \right)} \quad (3)$$

It is important to note that both occupancy load factor and passenger-relative load factor are averages, albeit weighted differently, of the load factors that vary from segment to segment according to the origin-destination profile of the service or route under consideration. While detailed analysis of that profile is warranted for many planning and operational activities, it would be convenient to develop a single and direct measure of the diversity of loading along the entire route, which enables universal comparison between services or routes. To this end, this paper defines *load diversity coefficient* of transit route R within distance-time window Z according to:

$$LD_{R,Z} = \frac{LF^{pr}_{R,Z}}{LF^{occ}_{R,Z}} \quad (4)$$

This measure defines how much greater passengers who travel aboard route R during distance-time window Z experience average load factor than does the route's operator. It offers a normalized measure of evenness of spread of passenger load for route R along distance-time window Z . The minimum possible value of 1.0 would reflect a constant passenger load aboard all services throughout Z , while a large value would reflect only isolated passenger loading aboard a service for a very brief time.

For a given service k , the following relationship between coefficient of variation in occupancy load factor along its run and load diversity coefficient may be proven:

$$LF^{occ}_{cv,k} = \sqrt{(LD_k - 1) \left(1 + \frac{1}{\left(\left(\sum_{i=1}^n t_{k,i} \right) - 1 \right)} \right)} \quad (5)$$

Similarly, Equations 2 and 4 may be solved to quantify coefficient of variation in occupancy load factor for route R within distance-time window Z as a function of coefficient of variation in occupancy load factor, provided that all buses have identical maximum schedule load, $P_{MSL,R}$:

$$LF^{occ}_{cv,R,Z} = \sqrt{(LD_{R,Z} - 1) \left(1 + \frac{1}{\left(\left(\sum_{k=1}^m \left(\sum_{i=1}^n t_{k,i} \right) \right) - 1 \right)} \right)} \quad (6)$$

It is noted that Equations 5 and 6 are relatively inelastic to the summation of segment times.

ENHANCEMENT TO ROUTE PASSENGER CAPACITY AND QUALITY OF SERVICE ASSESSMENT

While TCQSM (I) implies load factor as a point measure applicable to the individual segment, occupancy load factor and passenger-relative load factor are average measures along a route. TCQSM provides

general guidance how passenger load standards can be expressed and varied in relation to time of day, peak-of-the-peak, point in the route such as maximum load segment, and specified duration of time e.g. “no passenger should stand for more than X minutes”. TCQSM Exhibit 5-16 incorporates these considerations across six service levels, with commentary for each of the passenger and operator’s perspectives. Meanwhile, its capacity methodologies recommend that all potential locations of the maximum load segment be analysed for person capacity calculation.

While all potential maximum load segments need to be analysed using the origin – destination profile, especially for peak hour conditions, load diversity provides an additional characteristic that identifies to the operator how efficiently their resources are being utilized along the route and their passengers’ onboard experience. Based on Equations 1 to 6, Table 1 summarises how route coefficient of variation in occupancy load factor may be interpreted from the operator’s perspective of load diversity, and from the passengers’ perspective of average load factor relative to the operator’s.

TABLE 1 Interpretation of Coefficient of Variation in Occupancy Load Factor from Operator’s and Passengers’ Perspectives

Coefficient of Variation in Occupancy Load Factor	Operator’s Perspective of Loading Diversity	Passengers’ Perspective of Average Load Factor Relative to Operator’s (percentages relatively inelastic to segment times in Equations 5 and 6)
0	<ul style="list-style-type: none"> Point to point route or Exact balance/s between boardings, alightings at all stops Optimal loading pattern 	<ul style="list-style-type: none"> Same as operator
Up to 0.2	<ul style="list-style-type: none"> Extremely even balance/s between boardings, alightings at all stops Extremely productive loading pattern 	<ul style="list-style-type: none"> Up to 6% higher than operator
Up to 0.4	<ul style="list-style-type: none"> Very even balance/s between boardings, alightings at all stops Very productive loading pattern 	<ul style="list-style-type: none"> Up to 15% higher than operator
Up to 0.6	<ul style="list-style-type: none"> Good balance/s between boardings, alightings at all stops Productive loading pattern 	<ul style="list-style-type: none"> Up to 35% higher than operator
Up to 0.8	<ul style="list-style-type: none"> Fair to poor balance/s between boardings, alightings at all stops Unproductive to very unproductive loading pattern 	<ul style="list-style-type: none"> Up to 63% higher than operator
Up to 1.0	<ul style="list-style-type: none"> Very poor balance/s between boardings, alightings at all stops Highly unproductive loading pattern 	<ul style="list-style-type: none"> Up to twice as high as service/route average

Bunker (5) offered a passenger onboard comfort QoS table containing the two dimensions of occupancy load factor and passengers’ average travel time to enhance the assessment of passenger loading capacity and QoS based on TCQSM’s principles, but at the route level, both from the passengers’ and operator’s perspectives. Table 2 modifies that table from the passengers’ perspective, using passenger-relative load factor based on the theory of Equation 3, rather than occupancy load factor. The operator’s perspective remains unchanged from (5) where LF^{MLS} represents the measured or estimated load factor on the maximum load segment. Refer to (5) for theory to determine passengers’ average travel time.

The commentary in Table 2 is suited to assessment of an individual service operating along a route, or a design condition for a route such as a 15min peak. Should this commentary be applied to the

assessment of a route across with multiple services operating over an extended period such as a peak hour, it must be recognised that some services may perform better while others may perform worse.

TABLE 2 Conceptual Enhancement to Route Passenger Capacity and QoS Assessment from Passengers' and Operator's Perspectives

Passengers' Perspective					
Passengers' Average Travel Time					
Passenger-Relative Load Factor	Up to 15min	Up to 30min	Up to 45min	Up to 60min	Greater than 60min
Up to 0.33	• Average passenger has better than even chance of spare seat on short trip	• Average passenger has better than even chance of spare seat on medium trip	• Average passenger has better than even chance of spare seat on medium to long trip	• Average passenger has better than even chance of spare seat on long trip	• Average passenger has better than even chance of spare seat on very long trip
Up to 0.50	• Average passenger has better than 25% chance of spare seat on short trip	• Average passenger has better than 25% chance of spare seat on medium trip	• Average passenger has better than 25% chance of spare seat on medium to long trip	• Average passenger has better than 25% chance of spare seat on long trip	• Average passenger has better than 25% chance of spare seat on very long trip
Up to 0.67	• Average passenger can expect to sit on short trip	• Average passenger can expect to sit on medium trip	• Average passenger can expect to sit on medium to long trip	• Average passenger can expect to sit on long trip	• Average passenger can expect to sit on very long trip
Up to 0.89	• Average passenger has up to 25% chance of having to stand on short trip	• Average passenger has up to 25% chance of having to stand on medium trip	• Average passenger has up to 25% chance of having to stand on medium to long trip	• Average passenger has up to 25% chance of having to stand on long trip	• Average passenger has up to 25% chance of having to stand on very long trip
Up to 1.0	• Average passenger has up to 33% chance of having to stand on short trip	• Average passenger has up to 33% chance of having to stand on medium trip	• Average passenger has up to 33% chance of having to stand on medium to long trip	• Average passenger has up to 33% chance of having to stand on long trip	• Average passenger has up to 33% chance of having to stand on very long trip
Greater than 1.0	• All passengers experience crush loads throughout short trip	• All passengers experience crush loads throughout medium trip	• All passengers experience crush loads throughout medium to long trip	• All passengers experience crush loads throughout long trip	• All passengers experience crush loads throughout very long trip
Operator's Perspective					
Occupancy Load Factor	Up to 15min	Up to 30min	Up to 45min	Up to 60min	Greater than 60min
Up to $\frac{0.33}{(L_{FMLS}/L_{Focc})}$	• Unproductive service	• Unproductive service	• Unproductive service	• Unproductive service	• Unproductive service
Up to	• Unproductive	• Unproductive	• Marginally	• Productive	• Productive

$\frac{0.53}{(L_F^{MLS}/L_F^{occ})}$	service	service unless higher load factors occur on some segments	productive service if higher load factors occur on some segments	service if higher load factors occur on some segments	service if higher load factors occur on some segments
Up to $\frac{0.67}{(L_F^{MLS}/L_F^{occ})}$	• Marginally productive service if higher load factors occur on some segments	• Marginally productive service if higher load factors occur on some segments	• Productive service if higher load factors occur on some segments	• Productive service if higher load factors occur on some segments	• Productive service if higher load factors occur on some segments
Up to $\frac{0.83}{(L_F^{MLS}/L_F^{occ})}$	• Productive service if higher load factors occur on some segments	• Productive service if higher load factors occur on some segments	• Very productive service if higher load factors occur on some segments	• Very productive service if higher load factors occur on some segments	• Very productive service
Up to $\frac{1}{(L_F^{MLS}/L_F^{occ})}$	• Productive service	• Very productive service if higher load factors occur on some segments	• Very productive service if higher load factors occur on some segments	• Very productive service. • May generate complaints by standing passengers if higher load factors occur on some segments	• Very productive service. • May generate complaints by standing passengers if higher load factors occur on some segments
Greater than $\frac{1}{(L_F^{MLS}/L_F^{occ})}$	• Very productive service • Potential for some unreliability • Likely to generate some passenger complaints about overcrowding and/or pass-ups	• Very productive service • Potential for significant unreliability • Likely to generate complaints about overcrowding and/or pass-ups	• Significant unreliability likely • Certain to generate complaints about standing / overcrowding for long time periods and/or pass-ups	• Significant unreliability likely • Certain to generate complaints about standing / overcrowding for long time periods and/or pass-ups	• Significant unreliability likely • Certain to generate complaints about standing / overcrowding for long time periods and/or pass-ups

CASE STUDY DEMONSTRATION OF THEORY

This case study uses premium radial bus Route 222 in Brisbane, Australia after (5) to illustrate the theory of Equations 1 to 6. AFC boarding and alighting data from a hybrid smart-card touch-on/off and legacy on-board paper ticket sale system with a 100% sample was provided by Queensland Transport and Main Roads' TransLink Division for a normal 24 hour weekday in April 2012.

Figure 1 illustrates the location and characteristics of Route 222, which contains 12 segments over 12.9km (8.0mi). The outermost five are on-street bus segments on an arterial road corridor while the innermost seven are segments on a Bus Rapid Transit line. The nature of each stop was described in (5). At the time of data acquisition, Route 222 offered an off-peak 15 minute frequency between 05:00 and 23:30, and a 10 minute frequency in the peak direction during each of the two hour peak periods. Figure 2 illustrates the inbound schedule paths for a.m. peak, off-peak, and p.m. peak.

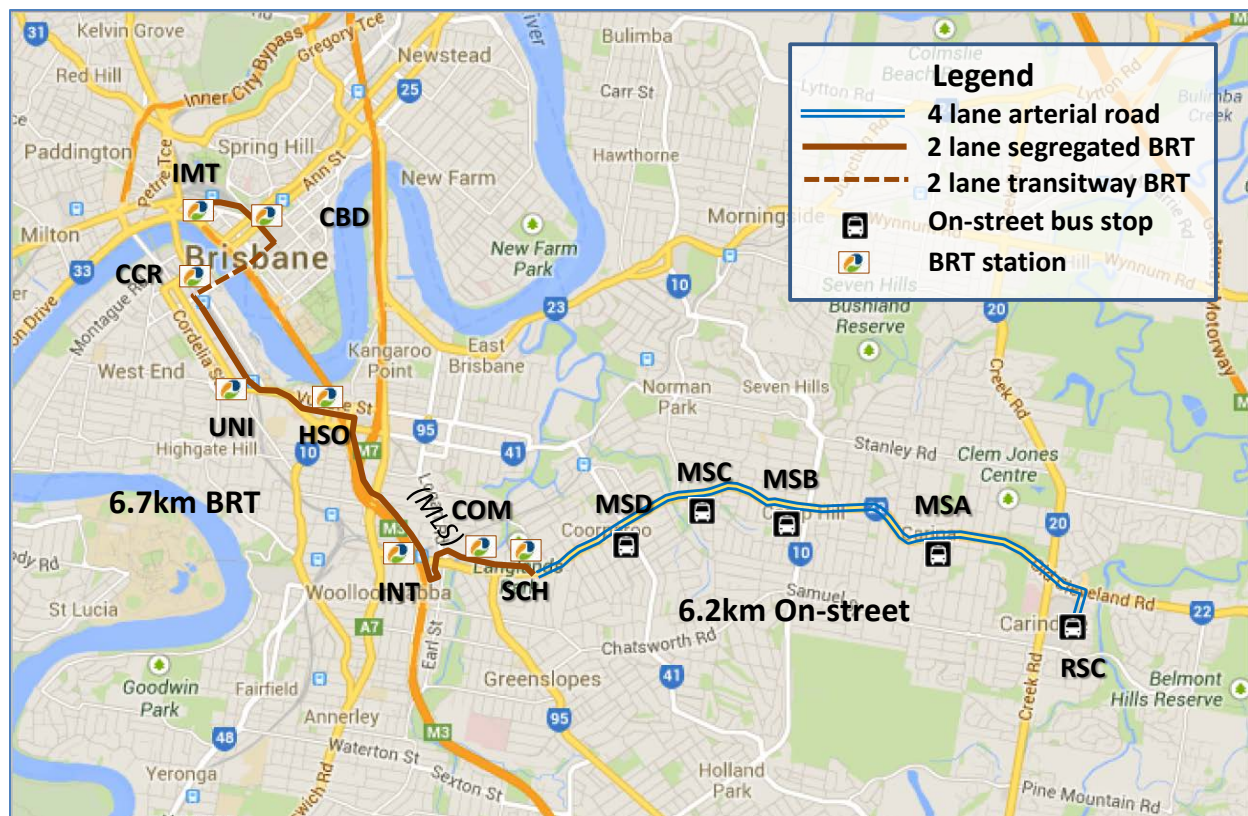


FIGURE 1 Case Study Route 222 Location in Brisbane, Australia, NOTE: 1km = 0.62mi.

A fleet of 12.5m (41.0ft) buses with 45 seats and 65p maximum schedule load was used on all Route 222 inbound services, aside from the highest demand morning service, for which a 14.5m (47.5ft) high capacity bus with 55 seats and an 85p maximum schedule load was used. Route 222 shares transit line with some other routes which for clarity are omitted from this analysis. Figure 3 (5) illustrates the inbound loading profile by hour across the study weekday, revealing a strong morning peak and softer evening peak. The maximum load segment was predominantly after station COM, which is upstream of major inner urban stations.

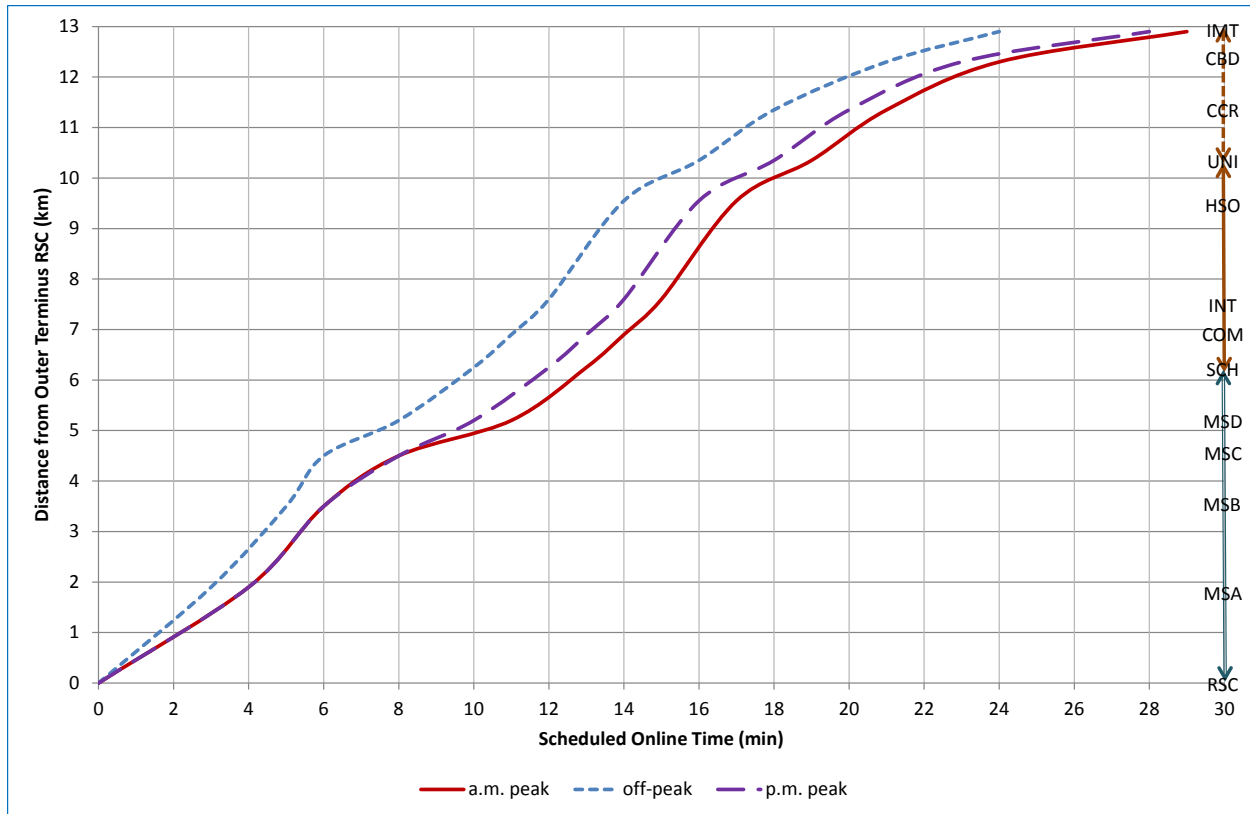


FIGURE 2 Route 222 Weekday Inbound Schedule Paths, NOTE: 1km = 0.62mi.

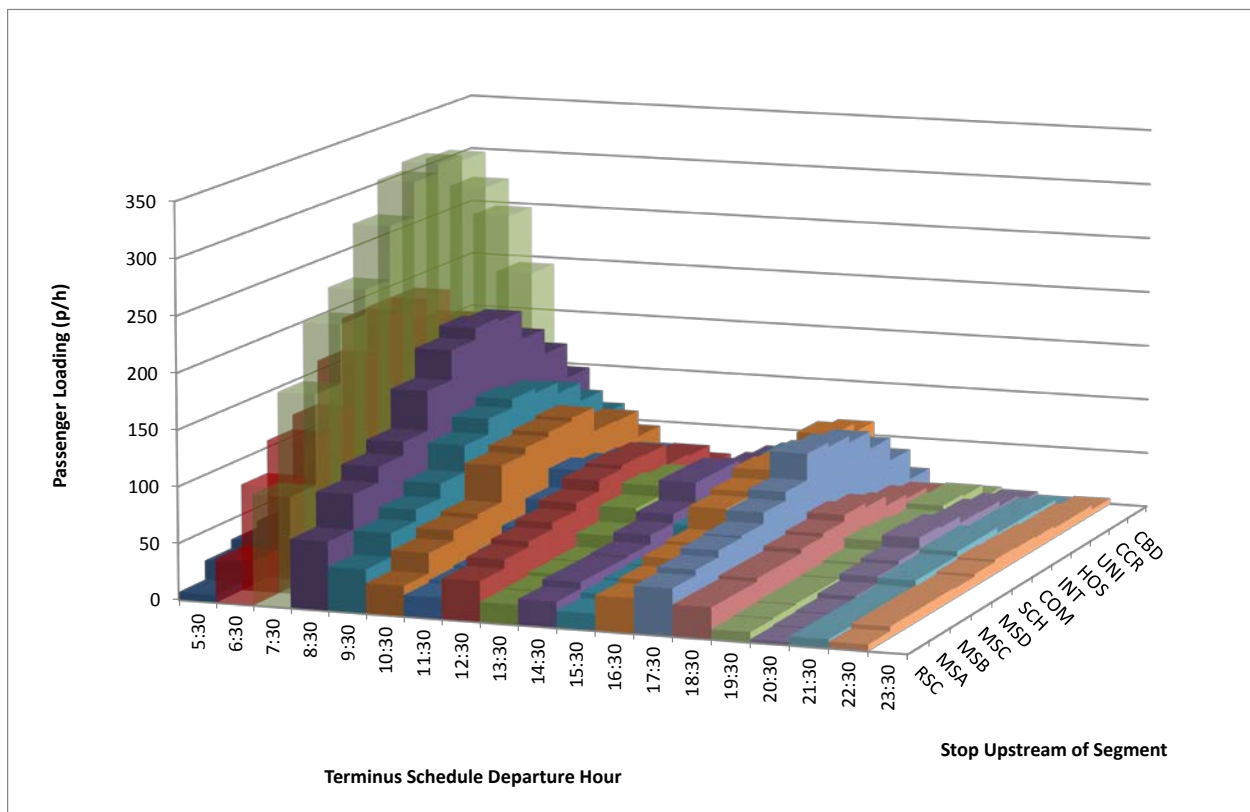


FIGURE 3 Route 222 Weekday Inbound Passenger Loading Profiles.

Relationships between Hourly Route Occupancy Load Factor, Passenger-Relative Load Factor, and Load Diversity Coefficient

Figure 4 illustrates Route 222's inbound occupancy load factor, passenger-relative load factor, and load diversity coefficient time histories by hour across the study weekday. Relative to the operator, during the a.m. peak hour just over half of passenger time-spaces offered along the route were utilized. By contrast, relative to the passengers on average two thirds of spaces or all seats were occupied. During the p.m. contra-peak hour, relative to the operator almost 80 percent of all time-spaces offered were unutilised. By contrast, relative to the passengers slightly under one third of spaces around them were occupied, meaning they were able to sit and did not need to sit next to others.

Inspection of the load diversity coefficient curve in Figure 4 reveals that on an hourly basis there was considerable variability along Route 222, more so during off-peak periods than the a.m. peak hour and p.m. contra-peak hour, during which time passengers tended to make longer journeys (5). Inverse correlation between occupancy load factor and load diversity coefficient was determined to be moderate across the study weekday, with r equal to -0.39.

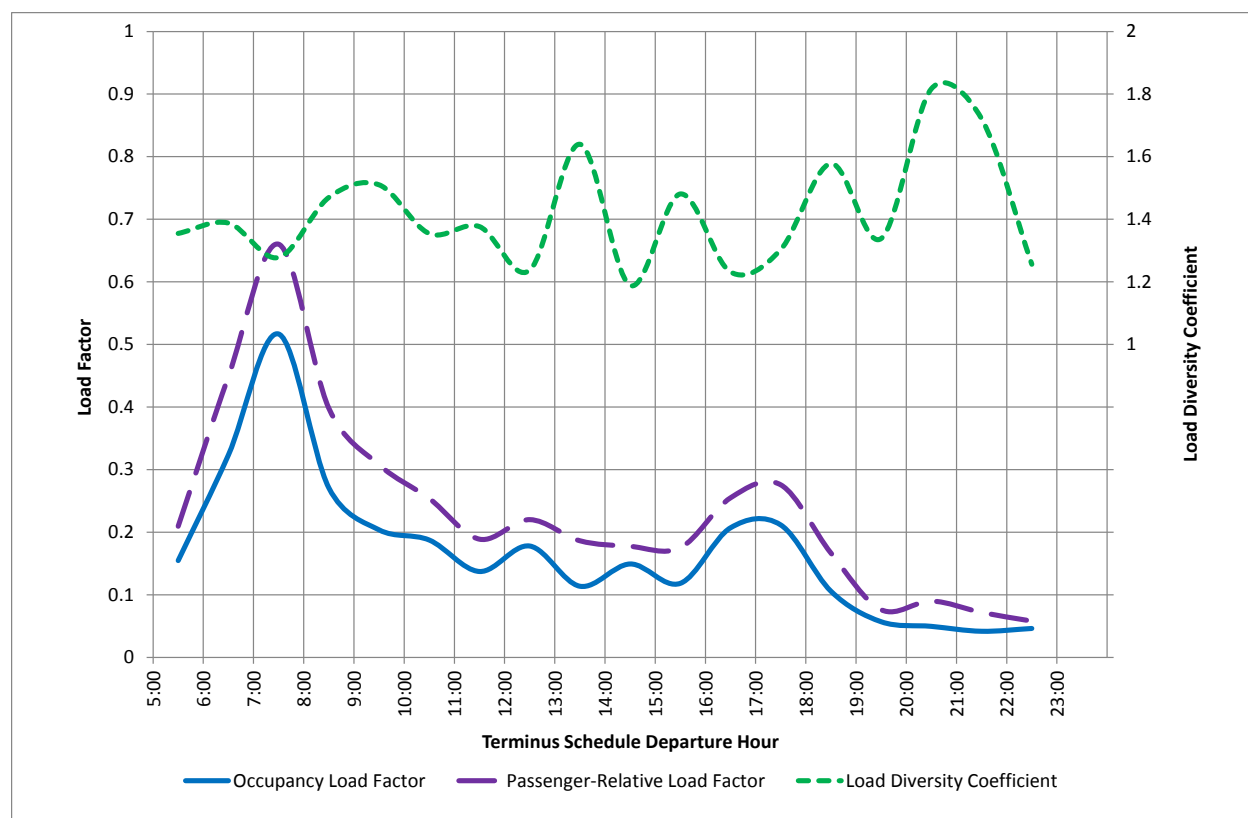


FIGURE 4 Route 222 Services Inbound Hourly Occupancy Load Factor, Passenger-Relative Load Factor, and Load Diversity Coefficient across Weekday.

Relationship between Hourly Route Coefficient of Variation in Occupancy Load Factor and Load Diversity Coefficient

Figure 5 illustrates the relationship between Route 222's inbound occupancy load factor and load diversity coefficient, where each data point represents one hour across the weekday study period. Also shown is the function generated using Equation 6 with a sum of in-service time equal to 96min

corresponding to the off-peak 15min headway. Not all data points precisely match this function, for instance because the sum of in-service time during the a.m. peak hour is 174min, while the sum during the late evening off-peak hour is 72min. Functions generated using such values align with the main function very closely so have been omitted for clarity. The relationship shows that passenger load diversity increases non-linearly with coefficient of variation of occupancy load factor.

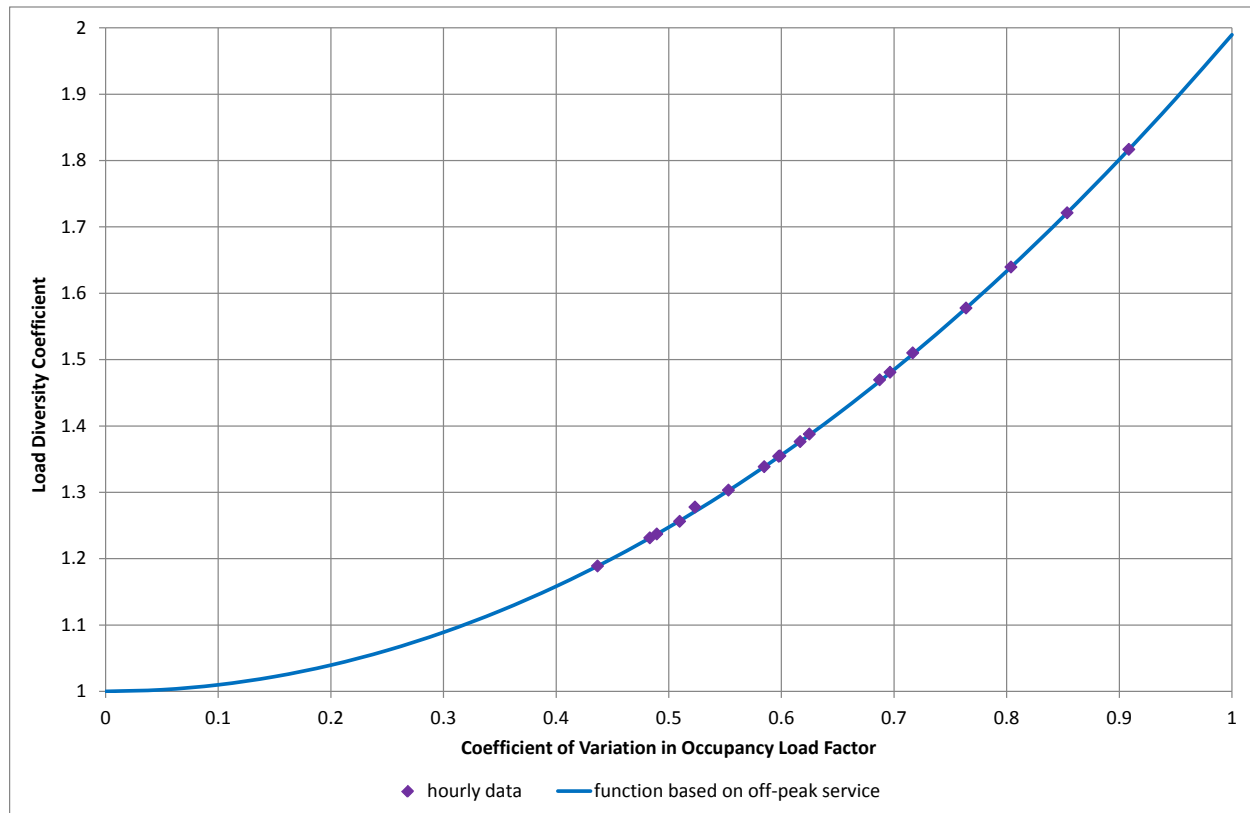


FIGURE 5 Route 222 Weekday Inbound Hourly Coefficient of Variation in Occupancy Load Factor vs Load Diversity Coefficient.

Peak Hour Improvement Treatment Assessment

The top chart of Figure 6 illustrates inbound load factor by segment measured on the six Route 222 services that operated during the a.m. peak hour commencing 07:00 from the origin terminus. Analysis of the data across all services found the ratio LF^{MLS}/LF^{occ} to consistently approximately equal 1.5.

Inspection reveals that the 7:05 service reached maximum schedule load on the segments downstream of stops SCH and COM, for a total schedule running time of 2min. However, the 7:25 service operated using the 75 space high capacity bus was most highly loaded, reaching crush loads on the successive segments downstream of stops MSD, SCH, COM and INT, for a total schedule running time of 6min.

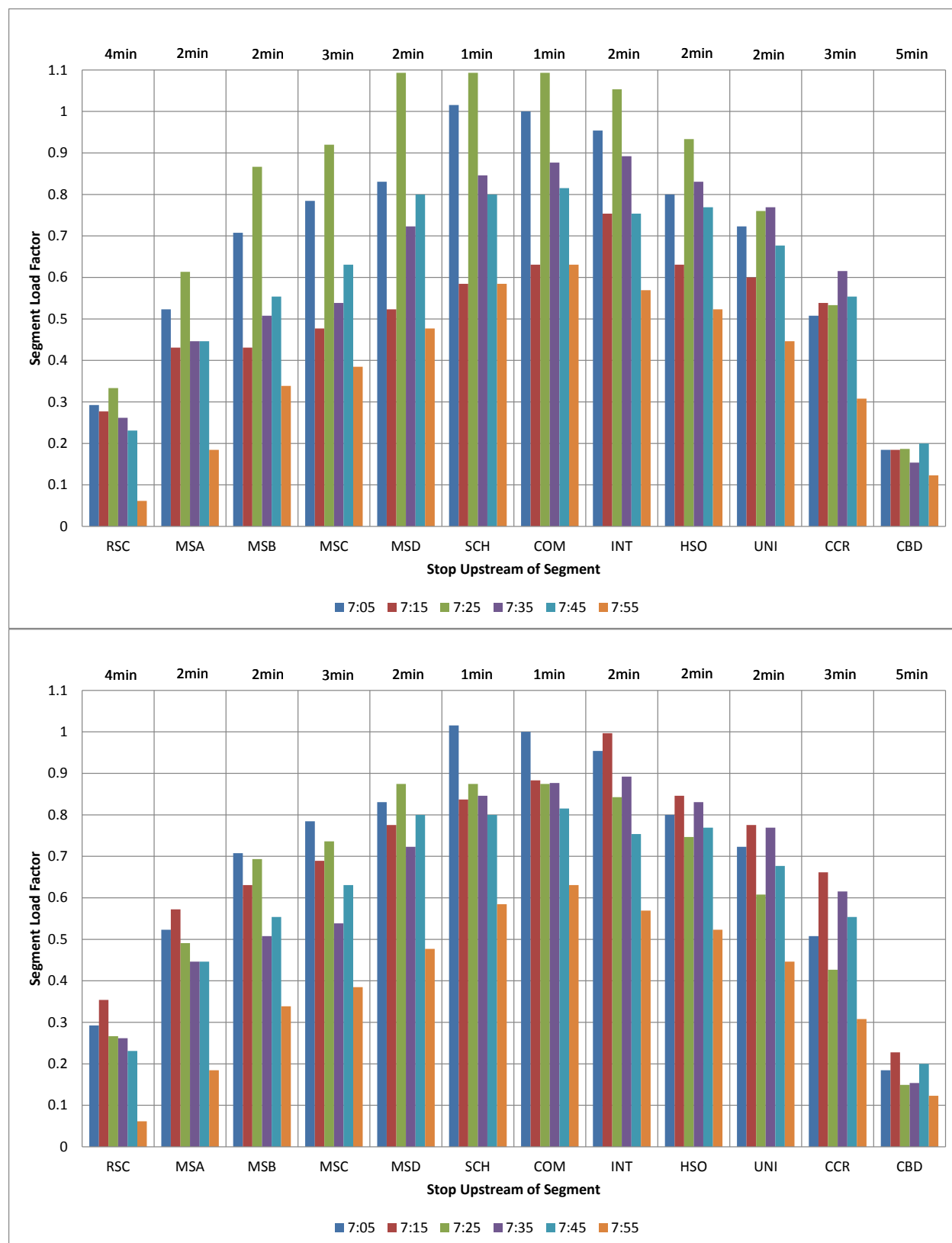


FIGURE 6 Route 222 Weekday A.M. Peak Hour Inbound Services' Load Factors by Segment and Scheduled Segment Running Times (top) Existing and (bottom) With Proposed 7:15 Service Holding Treatment).

Table 3 provides a specific examination on a service by service basis for this existing weekday a.m. peak hour (unshaded rows). The occupancy load factor for the 7:05 service was equal to 0.59, while its load diversity coefficient was equal to 1.22. From the operator's perspective this service had a productive loading pattern and delivered a very productive service. Comparing the passenger-relative load factor of 0.72 with the conceptual service levels of Table 2, on average passengers who used this service had up to a 25 percent chance of having to stand during their journey. Visual inspection of the data for this service reveals this to be influenced by the load factors exceeding the seated load factor threshold of 0.67 on the eight segments between stops MSB and CCR.

The occupancy load factor for the 7:25 service for which crush loading occurred across four successive segments was equal to 0.67, while the load diversity coefficient was equal to 1.24. From the operator's perspective this service had a productive loading pattern and delivered a very productive service despite potential for unreliability and pass-ups. The passenger-relative load factor of 0.83 compared with the conceptual service levels of Table 2 reveals that on average passengers who used this service had up to a 25 percent chance of having to stand during their journey. Visual inspection for this service reveals that this is influenced by very high load factors on the eight segments between stops MSB and CCR.

The top chart in Figure 6 suggests a likely cause of the very high loadings on the 7:05 and 7:25 services. In contrast to these services, the 7:15 service's load factors along all nine segments between MSA and CCR are low. The load diversity coefficient for the 7:15 service listed in Table 2 is also lower than those of the other services, indicating an atypically even load pattern between segments. This offers circumstantial evidence that the 7:05 service was running behind schedule and collected some of the native passenger demand of the 7:15 service. This likely caused the 7:15 service to run ahead of schedule along the route. Consequently, the 7:25 service appears to have collected some of the native 7:15 service passenger demand, who missed that service due to it running early. It is important to note that this is surmised from the AFC and schedule data, because AVL data was not available.

Inspection of the services' load diversity coefficients in Table 2 overall reveals quite even load patterns, which may be attributed to longer, peak hour commute journeys.

TABLE 3 Route 222 Weekday A.M. Peak Hour Inbound Service by Service and Hourly Passenger Loading Quality of Service (Existing & with 7:15 Service Holding Option)

Service Departing Upstream Terminus	Case/s	Occupancy Load Factor	Passenger-Relative Load Factor	Load Diversity Coefficient	Passengers' Perspective Service Level (Table 2)	Operator's Perspective Service Level (Tables 1 and 2)
7:05	Existing, and with 7:15 service holding	0.59	0.72	1.22	<ul style="list-style-type: none"> • Average passenger has up to 25% chance of having to stand on medium trip 	<ul style="list-style-type: none"> • Productive loading pattern • Very productive service
7:15	Existing	0.45	0.51	1.15	<ul style="list-style-type: none"> • Average passenger can expect to sit on medium trip 	<ul style="list-style-type: none"> • Very productive loading pattern • Productive service
	7:15 service holding	0.60	0.70	1.16	<ul style="list-style-type: none"> • Average passenger has up to 25% chance of having to stand on medium trip 	<ul style="list-style-type: none"> • Productive loading pattern • Very productive service
7:25	Existing	0.67	0.83	1.24	<ul style="list-style-type: none"> • average passenger has up 	<ul style="list-style-type: none"> • Productive loading pattern

					to 25% chance of having to stand on medium trip	• Very productive service, potentially unreliable and pass-ups
	7:15 service holding	0.54	0.66	1.24	• Average passenger can expect to sit on medium trip	• Productive loading pattern • Productive service
7:35	Existing, and with 7:15 service holding	0.53	0.65	1.23	• Average passenger can expect to sit on medium trip	• Productive loading pattern • Very productive service
7:45	Existing, and with 7:15 service holding	0.52	0.62	1.19	• Average passenger can expect to sit on medium trip	• Productive loading pattern • Very productive service
7:55	Existing, and with 7:15 service holding	0.32	0.42	1.33	• Average passenger has better than 25% chance of spare seat on medium trip	• Productive loading pattern • Productive service if higher load factors on some segments
Hourly (R, Z)	Existing	0.52	0.66	1.28	• Average passenger can expect to sit on medium trip	• Productive loading pattern • Very productive service
	7:15 service holding	0.52	0.65	1.25	• Average passenger can expect to sit on medium trip	• Productive loading pattern • Very productive service

The bottom chart of Figure 6 illustrates inbound load factor by segment on the six Route 222 services that operated during the a.m. peak hour commencing 07:00 from the origin terminus, modified here to reflect adoption of a holding strategy for the 7:15 service. To generate this scenario, two minutes of passenger travel demand from the 7:25 service was re-allocated to the 7:15 service. This scenario assumes that the late running of the 7:05 service could not be ameliorated, so its demand was not modified.

Inspection of the bottom chart reveals that the 7:15 service would have approached maximum schedule load on the segment downstream of stop INT, for a total schedule running time of 2min. However, the crush load on the 7:25 service on the successive segments downstream of stops MSD, SCH, COM and INT, would have been completely ameliorated on its operating 75 space high capacity bus.

Table 3 also lists the passenger load QoS characteristics and assessment by service for this weekday a.m. peak hour, with shaded cells reflecting the 7:15 service holding strategy. The occupancy load factor for the 7:15 service would increase to 0.60, while the load diversity coefficient would increase only very slightly to 1.16. From the operator's perspective this service would have a productive loading pattern and improve to deliver a very productive service. The passenger-relative load factor of 0.70 compared with the service levels of Table 2 reveals that on average passengers who use this service would have up to a 25 percent chance of having to stand during their journey under this holding strategy.

The occupancy load factor for the 7:25 service would decrease to 0.54, while the load diversity coefficient would remain at 1.24. From the operator's perspective this service would have a productive loading pattern and deliver a productive service. The passenger-relative load factor of 0.66 compared with

the service levels of Table 2 reveals that on average passengers who use this service would expect to be able to sit during their journey under this holding strategy.

From Table 3, the hourly occupancy load factor of this modified scenario would not change over the actual conditions. This presumes that all services maintain their scheduled segment running times while in service. However, the hourly passenger-relative load factor does reduce very slightly, due to the redistribution of both load factors and passenger loadings from the 7:25 to the 7:15 service. Accordingly, there is a slight improvement in the evenness of passenger loading along the route as shown by the slight decrease in hourly load diversity coefficient.

CONCLUSIONS

This paper advances our understanding of route passenger capacity and quality of service (QoS) by quantifying passenger-relative load factor and distinguishing it from occupancy load factor. This paper introduced load diversity coefficient as the ratio between the two load factor measures, which as a direct measure of the route's origin-destination profile defines how much greater passengers who travel aboard a route experience average load factor than does the route's operator through its bus drivers. It also quantified the theoretical relationship between load diversity coefficient and temporal coefficient of variation of load factor.

Two tables were developed that enhance route passenger capacity and QoS assessment. Table 1 interprets coefficient of variation in occupancy load factor across six service levels, from the operator's perspective of loading pattern and from the passengers' perspective of load factor relative to the operator's. Table 2 conceptualizes an enhanced passenger loading QoS assessment tool across six service levels, in two dimensions of passenger-relative load factor and average travel time from the passengers' perspective, and two dimensions of occupancy load factor and passengers' average travel time from the operator's perspective. These methodologies quantify the passenger's overall experience of comfort as a result of load during their time aboard. They can enhance existing methodologies for benchmarking and decision making regarding route and schedule design.

Using a case study premium radial bus route operating on a typical weekday in Brisbane, Australia, this study found some limited inverse correlation between load diversity coefficient and occupancy load factor, reflecting that during peak periods loading is less concentrated within the route.

In a practical setting, this theory and methodology could be adapted using spreadsheet analysis to a fixed schedule route. With schedule, boarding and alighting count data by stop is required, which is accessible from Automatic Fare Collection or Automatic Passenger Count systems.

The outcomes of this study provide valuable research directions. Routes having a variety of features should be studied to more fully inform capacity utilization and QoS assessment. Some research cited in (1) and (10) may be extended to assign value of time (VoT) dynamically during the passengers' journey as onboard loading conditions change and time spent aboard increases. In turn, VoT may be interpreted at the route level in order to offer an additional QoS measure that reflects passenger comfort through crowding, thereby assisting in broader econometric modeling of transit service quality.

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REFERENCES

1. Kittelson & Associates, Inc., Parsons Brinckerhoff, KFH Group, Inc., Texas A&M Transportation Institute, and Arup. *TCRP Report 165: Transit Capacity and Quality of Service Manual*, 3rd Edition. Transportation Research Board of the National Academies, Washington, D.C., 2013.
2. Vuchic, V. R. *Urban Transit: Operations, Planning, and Economics*. John Wiley and Sons, Inc., Hoboken, 2005.

- 1 3. Vuchic, V. R. *Urban Transit: Systems and Technology*. John Wiley and Sons, Inc., Hoboken,
2 2007.
- 3 4. Bunker J.M. High Load Transit Line Passenger Transmission and Productiveness Efficiencies. In
4 *Transportation Research Record: Journal of the Transportation Research Board*, No. 2351,
5 Transportation Research Board of the National Academies, Washington, D.C., 2014, pp. 85–94.
- 6 5. Bunker J.M. [occupancy load factor], XXXX.
- 7 6. Fu L., J. Yang, and J. Casello. Quantifying the Technical Efficiency of Paratransit Systems Using
8 the Data Envelop Analysis Method. In *Transportation Research Record: Journal of the*
9 *Transportation Research Board*, No. 2034, Transportation Research Board of the National
10 Academies, Washington, D.C., 2007, pp. 115–122.
- 11 7. Hassold S. and A. Ceder. Public Transport Time-tabling Based on Maximum-Load Points Using
12 Multisize Vehicles. In *Transportation Research Record: Journal of the Transportation Research*
13 *Board*, No. 2352, Transportation Research Board of the National Academies, Washington, D.C.,
14 2013, pp. 104–113.
- 15 8. Ji Y. and M. Zhang. Dynamic Holding Strategy to Prevent Buses from Bunching. In
16 *Transportation Research Record: Journal of the Transportation Research Board*, No. 2352,
17 Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 94–103.
- 18 9. Strathman J.G., T.J. Kimpel, K.J. Dueker, R.L. Gerhart, and S. Callas. Evaluation of Transit
19 Operations: Data Applications of Tri-Met’s Automated Bus Dispatching System. In
20 *Transportation*, No. 29, 2002.
- 21 10. Cats O., A.N. Larijani, Á. Ólafsdóttir, W. Burghout, I.J. Andréasson, and H.N. Koutsopoulos.
22 Bus-Holding Control Strategies: Simulation-Based Evaluation and Guidelines for
23 Implementation. In *Transportation Research Record: Journal of the Transportation Research*
24 *Board*, No. 2274, Transportation Research Board of the National Academies, Washington, D.C.,
25 2012, pp. 100–108.
- 26 11. Wardman, M. Public Transport Values of Time. In *Transport Policy*, Vol. 11, Issue 4, 2004, pp.
27 363–377.
- 28 12. Concas, S., and A. Kolpakov. *Synthesis of Research on Value of Time and Value of Reliability*.
29 Report BD54946. Florida Department of Transportation, Tallahassee, January 2009.
- 30 13. Tirachini A., Hensher D.A. and J.M. Rose. Crowding in Public Transport Systems: Effects on
31 Users, Operation and Implications for the Estimation of Demand. In *Transportation Research*
32 *Part A: Policy and Practice*, Vol 53, pp 36 – 52.
- 33 14. Carrasco N. Quantifying Reliability of Transit Service in Zurich, Switzerland. In *Transportation*
34 *Research Record: Journal of the Transportation Research Board*, No. 2274, Transportation
35 Research Board of the National Academies, Washington, D.C., 2012, pp. 114–125.
- 36 15. Furth, P.G., B. Hemily, T.H.J. Muller, and J. Strathman. *TCRP Report 113: Using Archived AVL-*
37 *APC Data to Improve Transit Performance and Management*. Transportation Research Board of
38 the National Academies, Washington, D.C., 2006.
- 39 16. Sun Y., and R. Xu. Rail Transit Travel Time Reliability and Estimation of Passenger Route
40 Choice Behavior: Analysis Using Automatic Fare Collection Data. In *Transportation Research*
41 *Record: Journal of the Transportation Research Board*, No. 2275, Transportation Research Board
42 of the National Academies, Washington, D.C., 2012, pp. 58–67.